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The hotspots of life cycle assessment for bioenergy: A review by social network analysis

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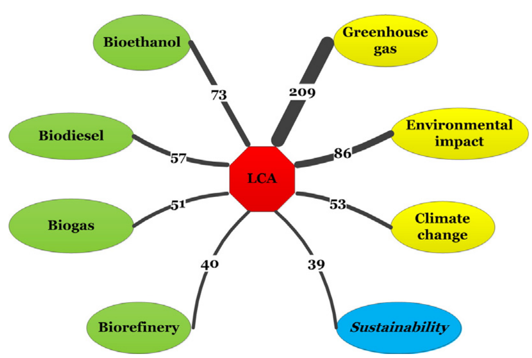
HIGHLIGHTS

- Certain characteristics of LCA for biomass were visualized.
- Provide a review on the evolution of LCA for bioenergy.
- The implication of LCA for bioethanol has showed a descending trend.
- Biogas could be the direction of LCA for bioenergy.

GRAPHICAL ABSTRACT

The co- occur weight between the high frequency keywords and LCA.



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ABSTRACT

The purpose of this paper is to provide an up-to-date bibliometric view about the current life cycle assessment (LCA) for bioenergy. The social network analysis (SNA) method was applied to study total 2367 publications in this field. The results showed the high frequency keywords related with the "LCA" for bioenergy included three categories: (1) Bioenergy production, such as "Biodiesel", "Bioethanol", "Biogas" and "Biorefinery"; (2) Environmental problems, such as "Greenhouse gas" (GHG), "Environmental impact", "Climate change"; (3) Environmental target: "Sustainability". This means that LCA methods have been widely used in assessing the environmental impact from various types of bioenergy production process. Specially, the "GHG" attracted more attention in this research area. According to the temporal trend of the high frequency keywords, "bioethanol" is the most significant hotspot keyword of implication LCA. However, it has become colder since 2011. The environmental performance of "biogas" and "land use" began to receive attention since 2015.The evolutionary co-words network showed that the boundary of hotspots became overlapped. We also found four clusters were identified from keywords networks, i.e. the biggest cluster Cluster (I) (central cluster node linkage was "Bioethanol-GHG"), followed by Cluster (II) (central cluster node linkage was "Biodiesel-Algae"), Cluster (III) (central cluster node linkage was "Biorefinery-Sustainability") and Cluster (IV) (central cluster node linkage was "Biogas-Anaerobic digestion"). This cluster analysis also showed that the implication of LCA for the relationship between "bioethanol" and "GHG" is the most important hotspot research field. Although "biogas" is the smallest cluster now, it could be the next important hotspot of implication LCA for bioenergy. This study provides an effective approach to obtain a general knowledge of the LCA for bioenergy and supports a deeper understanding of research directions in the future.

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1. Introduction

Climate change mitigation requires a shift from fossil energy resources to renewables, and bioenergy is considered one of the major potential resources (Bentsen and Møller, 2017). From global perspectives, a third of oil reserves, half of gas reserves and over 80% of current coal reserves should be reduced from 2010 to 2050 in order to meet the target of keeping global warming below 2 °C (Mcglade and Ekins, 2015). What's more, fossil-fuel power generation is a major contributor to worldwide carbon emissions, making up more than 24% of total GHG emissions (Odeh and Cockerill, 2008). Given the unsustainable nature of fossil fuels, in recent years, the importance of the production and use of biomass to generate power, heat, and fuels is increasing on a global scale (Dressler et al., 2012). Renewable bioenergy is viewed as one of the ways to alleviate the current global warming crisis. Moreover, the recent IPCC and Global Energy Assessment reported on and provided the more stringent mitigation scenarios heavily rely on a large scale deployment of bioenergy with CO_2 capture and storage called BECCS technology (Creutzig et al., 2015).

At the present stage, the deployment of bioenergy provides great potential to mitigate climate change, but it also poses considerable risks. The production of bioenergy requires fossil fuel input and causes environmental impacts. There is uncertainty about the impacts of the growth of bioenergy crops on ecosystem services (Dagmar and Pete, 2017). Without a complete accounting of net GHG fluxes, development and evaluating mitigation strategies are not possible. Life cycle assessment (LCA) is an analytical tool widely used today in evaluating the advantages and disadvantages of bioenergy. Further, LCA can help to set environmental and climate performance criteria and standards for bioenergy and biofuels (Bright et al., 2012). Fig. 1 is the LCA technology framework. It follows the IOS14001 system standard. LCA is widely used in evaluating various products or projects related to environment. For example, Zuo and Zhao (2014) and Zuo et al. (2017) analyzed green building from a life-cycle perspective; Wang and Teah (2017) conducted a life cycle analysis about a small-scale horizontal axis wind turbines; Qi et al. (2017) carried out a case study on the life cycle assessment of recycling industrial mercury-containing waste.

There are lots of literatures investigating on the bioenergy, too. Mao et al. (2015a, 2015b) characterizes the body of knowledge on biomass energy from 1998 to 2013 by employing bibliometric techniques based on the Science Citation Index (SCI)databases; Valdez-Vazquez et al (2017) proposed a sustainability evaluation framework for bioenergy production systems; Zhao et al. (2011, 2016) established a "Five Forces" model as the analytical framework to investigate the competitiveness of the biomass power industry. Bentsen and Møller (2017) studied solar energy conserved in biomass. Most researches focused on the specific topic of raw materials, environmental impacts, production technologies, and economic benefits, respectively. However, few studies have reported on the overall hotspots and development trends of the research of LCA for bioenergy by bibliometrics.

Bibliometric methods are now firmly established as scientific specialties and are an integral part of research evaluation methodology especially within the scientific and applied fields (Ellegaard and Wallin, 2015). Through statistical analysis of a large number of data, the research hotspots and key points can be obtained. Bibliometric shows the current research characteristics in the form of knowledge map. The social network analysis (SNA) is an excellent bibliometric method. It can be applied to study sets of nodes (keywords) and links (co-word relationships). The analysis of co-word network can better show visual representation of a citation network, helping readers identify significant movements in research fronts and emerging research fields (Choi et al., 2011).

The objective of this study is to present the comprehensive publication status and hotspots about LCA for bioenergy by the SNA method. These results will not only provide a better understanding of global hotspots in the specific research related to the LCA for bioenergy, but may also provide useful information to broaden research area of bioenergy.

2. Data resource and methodology

2.1. Data resource

The data was retrieved from the web of science core collection database, in which Science Citation Index (SCI), Social Science Citation Index (SSCI), Conference proceedings Citation Index-Science (CPCI-S) and Conference Proceedings Citation Index-Social Science & Humanities (CPCI-SSH) were applied. These four databases generally were recognized as influential database, whose large amount of data can meet the requirements of study and research. We retrieved publication data from titles, abstracts and keywords of those papers in these four databases.

The specific steps are as follows: 1) data download; We entered web of science database and selected web of science core collection, then typed "("LCA" or "life cycle assessment") and ("biomass" or "bioenergy" or "biofuel")" in "topic" field. Considering there are fewer articles related to our topic before 2000, we retrieved articles that were published from 2000 to 2017. 2) Data collation; all literatures were located and stored in a dedicated folder. Some noise literatures have been deleted, such as correction, letter, book chapter, reprint, editorial material and so on, which may lead to some deviation on our results. After finishing the two steps, 2367 articles were obtained.

To avoid the repetition or messes brought up by nonstandard expressions, this paper used some methods to pre-treat all the keywords:

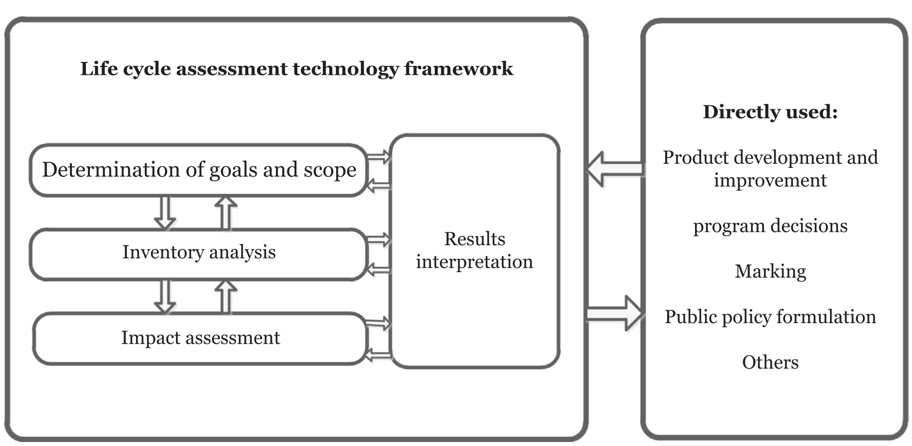

Fig. 1. The life cycle assessment technology framework.

1) combine the keywords that share the same meanings but use different descriptions such as LCA and life cycle assessment, CO_2 and CO_2 emissions; 2) singular or plural keywords such as biofuel and biofuels. A total of 4520 author keywords were supplied by 2367 articles.

2.2. Methodology

SNA methods were employed in order to analyze the trends and characteristics of researches related to LCA for bioenergy, including co-word analysis and small world theory. The pioneers of SNA came from sociology, social psychology and anthropology. It is based on the assumption that the importance of relationships among interacting units. It provides a precise way to define important social concepts and it has been developed to a mathematical analysis by graph theory in mathematics field (Zhang et al., 2015). In recent years, many scholars use social network to analysis citation networks or cooperation networks. Li et al. (2017) applied SNA to research keywords networks form "small world" In bibliometrics. SNA can show the relationships between keywords, authors and institutions. Besides, it also can explain the relationship ties and the position of each node in the networks. The Bibexcel and Gephi software are popular tools for SNA method, and co-word analysis and "small-word" theory indicators are the major analysis contents of SNA method.

2.2.1. Co-word analysis

Co-word analysis is a content analysis technology that uses patterns of co-occurrence of pairs of items (i.e., words or noun phrases) in a corpus of texts to identify the relationships between ideas within the subject areas presented in these texts (He, 1999). The two keywords that exist in the same paper show the links between the topics (Ding et al., 2001). Co-word analysis mainly has two steps: firstly, pick out the keywords with high frequency according to a threshold setting; then count the frequency of the two different keywords appearing in one article by Bibexcel software (Wang et al., 2014).

Currently, many scholars applied co-word analysis for visualizing the inner structure of one special field. For example, Wang et al. (2017) applied co-word network to analysis the interactions between technological and academic research in accomplishing low carbon transformation; Mao et al. (2015a, 2015b) mapped the research patterns of the environmental health literature by co-word analysis, which identifies global characteristics in environmental health research; Luo et al. (2017) employed co-word analysis to map the research topic system of soil heavy metal pollution bioremediation during the period of 1997–2016. Visibly, co-word analysis is useful in looking for communities and clusters in a discipline. In this paper, we also use co-word analysis to characterize the structure of LCA for bioenergy field during 2000–2017. The co-words network consists of three elements, i.e. nodes, lines, and clusters. These three elements are the focus of network analysis. Each node has a degree (D) which means the number of lines connected to a node and is visualized as the size of node. Node with larger size means it has stronger interconnection with other nodes and plays more important role in the network. The line between nodes represents the connection between them. The more closely two nodes relate, the thicker a line is. This is evaluated as a larger weight (W) of the line. The clusters are employed to distinguish different categories of research hotspots by modular networks. Those keywords in the same cluster usually have strong correlation (Li et al., 2017).

2.2.2. "Small-word" theory

The small world was defined as a network structure by a graph with nodes and links (Watts and Strogatz, 1998). The small world measure can be operationalized through the function of "Modularity", whose indicator is Q. The modularity of a partition is a scalar value between −1 and 1 that measures the density of links inside communities as compared to links between communities (Blondel et al., 2008). Besides, the average clustering coefficient, along with the average shortest path, can indicate the small world effect, too. When a network has a short average distance and high clustering coefficient, this network has a small world effect. Average path length is the average graph-distance between all pairs of members (Zhu and Guan, 2013). Average clustering coefficient and average path length are indicators of the whole network.

The clustering coefficient (C_i) is the ratio of the actual number of lines (L_i) between a node i and another node in the network and the maximum number of lines between it and all other nodes. Assume node i has W_i edges in the network, so there are most W_i (W_i-1)/2 edges. Therefore, the clustering coefficient can be expressed as:

$$C_i = \frac{2L_i}{W_i(W_i-1)} \tag{1}$$

The average clustering coefficient C of a whole network is expressed as:

$$C = \frac{1}{N}\sum_{i=1}^{n} C_i \tag{2}$$

The average clustering coefficient describes the properties of a generic node. The bigger it is, the better relationship between adjacent nodes.

D (i, j) is defined as the number of shortest edges connecting a pair of nodes i and j, then the total distance δ(N) is expressed as.

$$\delta(N) = \sum\nolimits_{1 \le i \le j \le N} D_{ij} \tag{3}$$

The average path length is then expressed as

$$S(N) = \frac{2\delta(N)}{N(N-1)} \tag{4}$$

The bigger it is, the more number of the edges, and the broader connections between every two nodes. The smaller it is, the less number of the edges, and the more limited connections between every two nodes.

3. Results and discussion

3.1. The hotpots research field applied LCA

To reveal the hot sections applied by LCA in bioenergy field, this paper compared the top 8 co-occurrence weight keywords with LCA (Fig. 2). According to the significance of these high frequency keywords, they could be grouped into three categories as below. This means that LCA methods have been widely used in assessing the environmental impact of various bioenergy productions. We separated the 8 keywords to three categories.

3.1.1. Bioenergy production

"Biodiesel", "bioethanol", "biogas" and "biorefinery" all belonged to this category. They are new-type biofuels that are widely used in transport, electricity and fuel cell. As shown in Fig. 2, we can see that the weight between bioethanol and LCA is the thickest in this category. The bioethanol production can offer environmentally favorable or equivalent profiles comparing with traditional ethanol production (Ren et al., 2015). Raw materials for ethanol production have corn grain, corn stover, lignocellulose, and waste paper, etc. (Morales et al., 2015).

Biodiesel and LCA are the second closest keywords in this category. Biodiesel as the most potential biofuel to substitute fossil diesel as a transport fuel has received great attention in China (Hou et al., 2011). The development of biodiesel has the potential to decrease the reliance on fossil fuel. Typical raw materials of biodiesel are edible oils like rapeseed and soybean oil. Transport distance, raw materials, edible oils yield

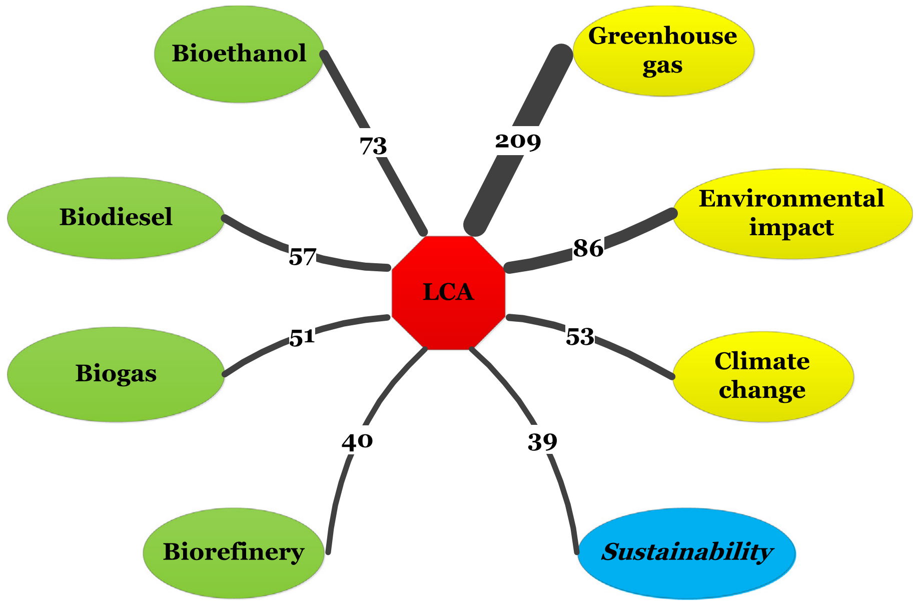

Fig. 2. The co-occurrence weight between the high frequency keywords and LCA.

and content had significant influence on the life cycle environmental performance of biodiesel.

The research of LCA for biogas is relatively weaker than that of bioethanol and biodiesel. The LCA for biogas mainly concentrated on the following four aspects: production mode; raw material resources; environmental inventory; engineering benefit. Landfill, anaerobic digestion, and CHP (combined heat and power) are the popular technologies for biogas production. Livestock, food waste, cattle feed, organic waste, agriculture residue, municipal waste, waste paper are the raw materials to produce biogas (Carvalho et al., 2017). Further, it is worth noting that air pollution and climate change are the main contents of environmental inventory from biogas (Jin et al., 2015). Besides, commercial scale, industrial scale, regional factors and power plant, and landfill capacity are the main factors affecting engineering benefit.

Biodiesel, bioethanol and biogas are major products of biorefinery technology. In biorefinery, almost all types of biomass feedstocks can be converted to different classes of biofuels and biochemicals through jointly applied conversion technologies (Cherubini and Jungmeier, 2010). However, the weight between LCA and biorefinery is the weakest, indicating that the implications of LCA focus on the products rather than technologies.

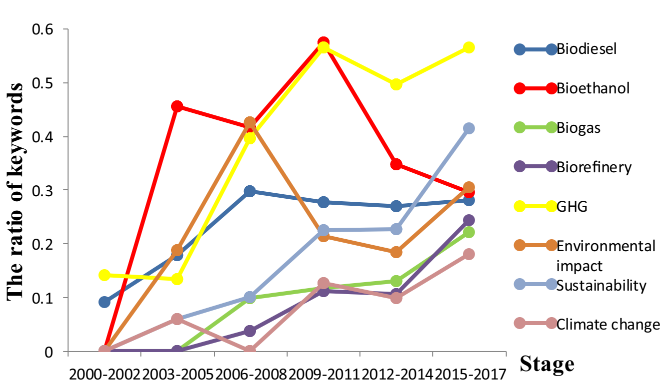

Fig. 3. Temporal trend of the high frequency keywords related to LCA. Note: The keyword frequencies were normalized by the number of publications in each stage.

Biorefineries encompass a whole range of different-sized installations to reach a complete utilization of several biomass ingredients. An important stage in biorefinery system is the provision of a renewable, consistent and regular supply of feedstock. Carbon- based raw materials for biorefinery could be divided into four resources: 1) forest; 2) aquaculture (seaweeds and algae); 3) agriculture (special crops and residues); 4) industries and households (municipal solid waste and wastewater). There are some researches measuring biorefinery system using life cycle assessment approach (Gasol et al., 2009; Wang et al., 2013), which takes into account all the input and output flows occurring along the production chain (Cherubini and Jungmeier, 2010). The major question in the assessment of biorefinery systems is how utilization of different types of biomasses will affect the environmental sustainability. Since climate change mitigation and energy security are the two most important driving forces for biorefinery development, the assessment focused on greenhouse gas (GHG) emissions and cumulative primary energy demand (distinguished into fossil and renewable). The other environmental impact categories (e.g. sharp decline in biodiversity, eutrophication, etc.) are assessed in many articles as well.

3.1.2. Environmental problems

This category included "greenhouse gas" (GHG), "climate change" and "environmental impact". They are the important environment issues. The thickest line (W = 209) is between nodes "LCA" and "greenhouse gas", implying these two keywords co-occur in articles most frequently. GHG emissions are the most important anthropogenic source of climate change. In the process of LCA for bioenergy, GHG is the core content, which suggests it has become a hottest problem and scholars make much account of it. The second thickest line (W = 86) is between nodes "Environmental impact" and "LCA". "Environmental impact" includes the whole environmental performance on water, air, land and ecosystem.

3.1.3. Environmental target

"Sustainability" is the goal of achieving global sustainability to meet society's current needs by using Earth's natural resources without compromising the needs of future generations. It is composed of ecological sustainability, economic sustainability and social sustainability. The rise of renewable energy and the popularity of LCA are all necessary steps to achieve sustainable goals.

3.2. Temporal trend of the high frequency keywords related to LCA

3.2.1. Keywords frequency analysis

We analyzed the temporal trend of the top 8 high frequency keywords related to LCA (see Fig. 3). The ratio of "GHG" experienced a multiple increase until the stage 2009–2011. It is worth noting that the ratio of "Bioethanol" experienced sharp increase from 2000 to 2011 compared with other keywords. After this stage, the "Bioethanol" began to decrease until now. This means although bioethanol is a hotspot of implication on LCA, it has become colder since stage 2009–2011. The trend of "Environmental impact" is similar to "GHG" and "Bioethanol". It also increased sharply during the stage 2000–2008 and decreased from the stage 2009–2011. The other five keywords "Biodiesel", "Sustainability", "Biogas", "Biorefinery" and "climate change" kept the similar trend of increase since 2000.

3.2.2. Keywords network analysis

We chose the top 30 high frequency keywords related to LCA to undertake cluster analysis by using the "Modularity" function in Gephi. Fig. 4 respectively gives the hot topic words and evolutionary co-words network at different stages. According to the formulas (1)–(4), the indicators of modularity, average cluster coefficient and average path length about every stage were calculated (Table 1).

3.2.2.1. 2000–2002. This stage has 6 clusters. This indicated it is the initial stage of the application of LCA on bioenergy. The number of keywords in each cluster is almost equal except the "biofuel" cluster, which only included itself. Besides, the node degree of each keyword is also relatively equal from 3 (biomass) to 1 (biofuel). The connection between clusters is not strong. "Biomass", "GHG", "biofuel" had begun to show their central status with high node degree.

3.2.2.2. 2003–2005. In this stage, the number of clusters increased to 7, which indicates there were more new research interests. For example, "CO_2" and "environmental impact" clusters appeared first time, indicating authors began to concentrate on environmental performance. In addition, "eutrophication", "avoided emissions" as a keyword, represented a single cluster, respectively. The new keywords "allocation" and "paper" composed of a new cluster. The "biomass" and "GHG" were still the main clusters and they became more prominent. There were many newly added keywords such as "climate change", "sustainability", "industrial ecology", "Kyoto protocol" in different clusters. Accordingly, many keywords disappeared or joined into other clusters. For example,

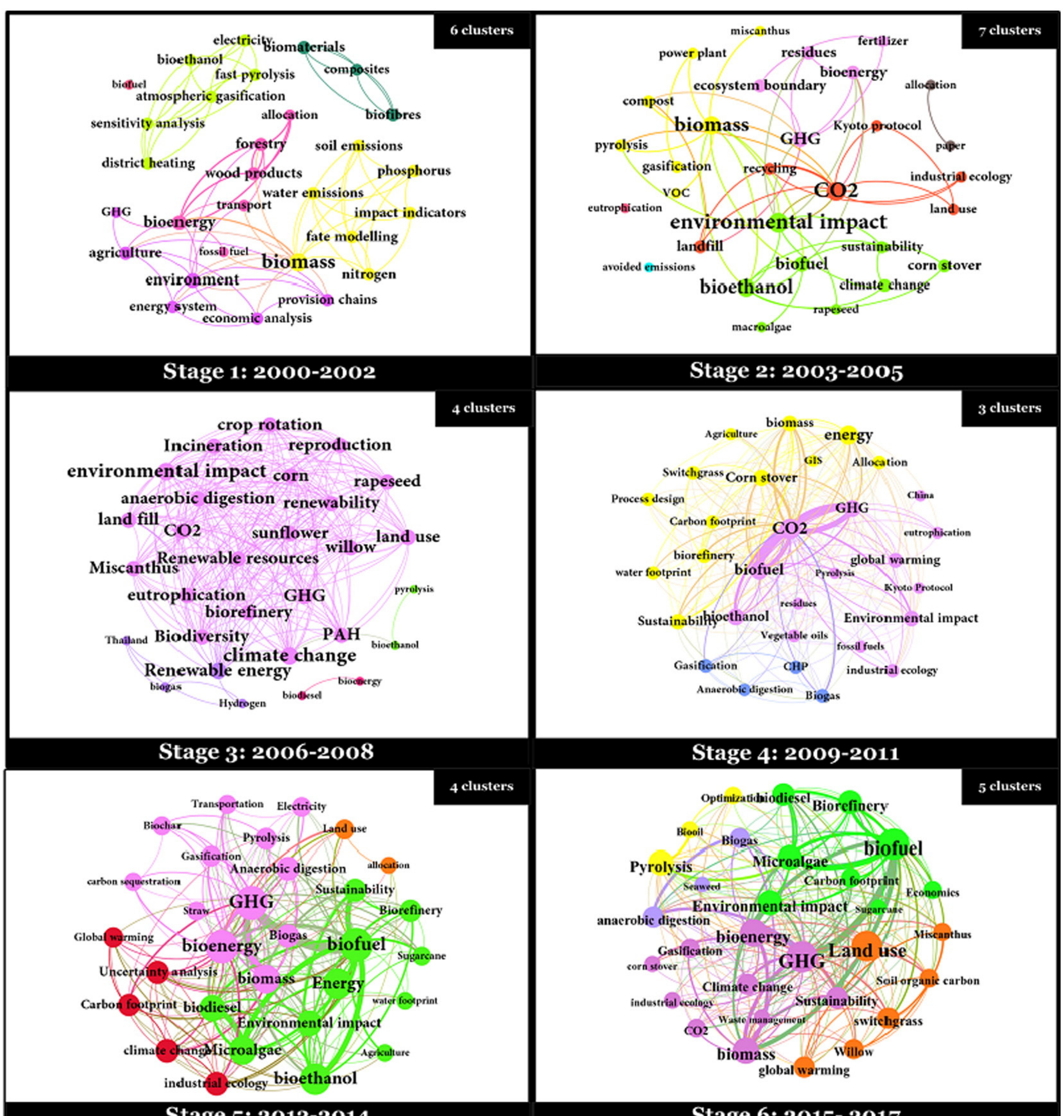

Fig. 4. The evolutionary co-words network.

Table 1
The small world network indicators of every stage.

Stages	Modularity	Average path length	Average clustering coefficient
Stage 1: 2000–2002	0.568	1.496	0.511
Stage 2: 2003–2005	0.438	3.096	0.262
Stage 3: 2006–2008	0.056	1.452	0.441
Stage 4: 2009–2011	0.121	1.841	0.624
Stage 5: 2012–2014	0.118	1.788	0.402
Stage 6: 2015–2017	0.12	1.885	0.387

"agriculture", "district heating", "nitrogen" disappeared, and "biofuel" added to "bioethanol" cluster. "Bioenergy" entered into "GHG" cluster. Besides, clusters started to build new connections gradually.

3.2.2.3. 2006–2008. The four clusters were identified from keywords networks in this stage. Some immature clusters in stage 2003–2005 disappeared or merged to other mainstream clusters. What's more, the degree of all nodes in this stage was much higher than the previous one. For example, the degree of "landfill" in the previous stage increased from 4 to 21. The degree of "eutrophication" also increased sharply from 2 to 22. This stage has a notable phenomenon that the purple cluster took up nearly 80% of all nodes number. "Climate change", "biorefinery" were two new nodes added to this cluster. "Environmental impact", "CO_2" and "GHG" were the central nodes in the purple cluster, indicating a closer relationship among them was forming. Many raw materials for biomass appeared in this cluster such as "corn", "miscanthus", "sunflower" and "willow". It is worth noting that the "Renewable energy" appeared as a central node with the highest node degree in a new cluster.

3.2.2.4. 2009–2011. There were only three clusters left in this stage. Great changes have taken place in this stage. Firstly, in "CO_2" cluster, the new nodes "China", "global warming", "vegetable oils" appeared. The line between "CO_2" and "biofuel" was the strongest and the line connecting "CO_2" and "GHG" was the second thickest. Secondly, "Sustainability", "GIS", "corn stover", "carbon footprint", "process design", "switchgrass" increased to a new cluster. "Gasification", "CHP", "biogas" and "anaerobic digestion" made up a new cluster. "Kyoto protocol" appeared again. Maybe this stage was just close to the first commitment period of The Kyoto Protocol (from 2008 to 2012). In all, there were many concepts (industrial ecology, carbon footprint, water footprint), environmental issues (global warming, environmental impact, eutrophication) and feedstocks (corn stover, switchgrass, residue, agriculture, vegetable oils) in this stage.

3.2.2.5. 2012–2014. Four clusters emerged in this stage. However, the notable feature in this stage was the area of every cluster expanded and different cluster began to overlap. It indicated the connections between these hot fields became strengthened. This stage mainly concentrated on biomass related products and technologies. Environmental performance became not so notable. What's more, the cluster division was clearer than before. The line between "GHG" and "biofuel" was the thickest ($W = 21$). However, the two keywords were located in two different clusters, respectively. This indicates though the relationship between "GHG" and "biofuel" is closest, the internal density of their respective clusters is greater than any external clustering density. "Microalgae", "sugarcane" as new keywords appeared and "water footprint", "biorefinery" also turned into this cluster from other cluster. "GHG" cluster consisted most technologies and products. "Land `use" and "allocation" was the smallest cluster in this stage, which had very little contact with other clusters. The weight between them is also weak ($W = 1$).

3.2.2.6. 2015–2017. A new cluster added on the basis of the front stage. "Land use" cluster expanded obviously, including 6 nodes in this stage. At the stage 2012–2014, there were only two nodes. The "GHG" cluster and "biofuel" cluster both reduced. "Anaerobic digestion" and "biogas" made up a new cluster. "Pyrolysis" also separated from the "GHG" cluster and created a new cluster. On the whole, this stage has experienced a relatively small change in both node degree and cluster situation. "GHG" is still the heavy node after a series of stages and more important, illustrating public awareness of GHG continues to heat up. "Land use" has appeared in 2003–2005, 2006–2008, 2012–2014, and 2015–2017 stages with increasing degree and finally became an independent cluster. This suggests during the LCA process, the environmental performance of land use began to receive attention. Besides, there are still some keywords that exist throughout the all research filed, such as "anaerobic digestion", "pyrolysis".

From Table 1, we can see that the modularity in 2000–2002 and 2003–2005 is over 0.3, indicating those communities in the two stages formed better convergence. In 2006–2008, the modularity became very small, however, for the rest of the stage, the modularity stayed at a stable level of 0.11–0.12, which suggests the LCA network decomposition reaches saturation level. As for the average path length, we can see that the index is presenting a cyclical fluctuation. From 2000–2002 to 2003–2005, the average path length increased. With the nodes number increasing in stage 2, the relationship between new nodes and old nodes had not established linkages. This caused the average path length in stage 2 became longer than that in stage1. Then the linkages between new nodes and old nodes strengthened in 2006–2008. Therefore, the average path length decreased from 2003–2005 to 2006–2008. However, in 2009–2011, some other new nodes appeared. Therefore, the average path length of the whole network increased. Similarly, the stage 5 and stage 6 have the same principle as the front stages.

The average clustering coefficient also waved largely. In 2000–2002, it is 0.511and in 2003-2005, it is 0.262. Many new keywords appeared. The relationship among those keywords became weaker. Then again, the average clustering coefficient gradually increased in the following two stages, indicating the connections among keywords strengthened. In 2009–2011, the average clustering coefficient reached the maximum. Then it began to drop since 2012–2014.

3.3. Four categories of research topics

We retrieved co-occurrence of the 88 top keywords accorded with their degree. The results show that keywords degree distributed widely, from 87 (GHG) to 10 (seaweed). But only the degree of GHG is over 80, all other keywords degree is lower than 50. The number of keywords in the 10–20 degree is 51, which is 58% the total number of nodes. From Fig. 5, we can see that these 88 top keywords are obviously grouped onto four main topics. Firstly, in the cluster (I), there were 42 keywords, taking up nearly half of all keywords numbers. The core keywords are "GHG" and "bioethanol", suggesting the research about this topic is the hotspot. The cluster (II) is the second biggest research area in LCA for biomass. This cluster could be summarized as the topic of using microalgae to produce biodiesel. Biodiesel and microalgae had the strongest connection. Biorefinery and sustainability were shown as the central nodes in the cluster (III). They also had a strong connection. The sustainability of biomass production process attracted more attention. Moreover, this research still has a potential prospect. The cluster(IV) is the smallest cluster among four clusters. There were only 11 keywords. Cluster(IV) concentrated on anaerobic digestion technology and biogas production. The interest in anaerobic digestion

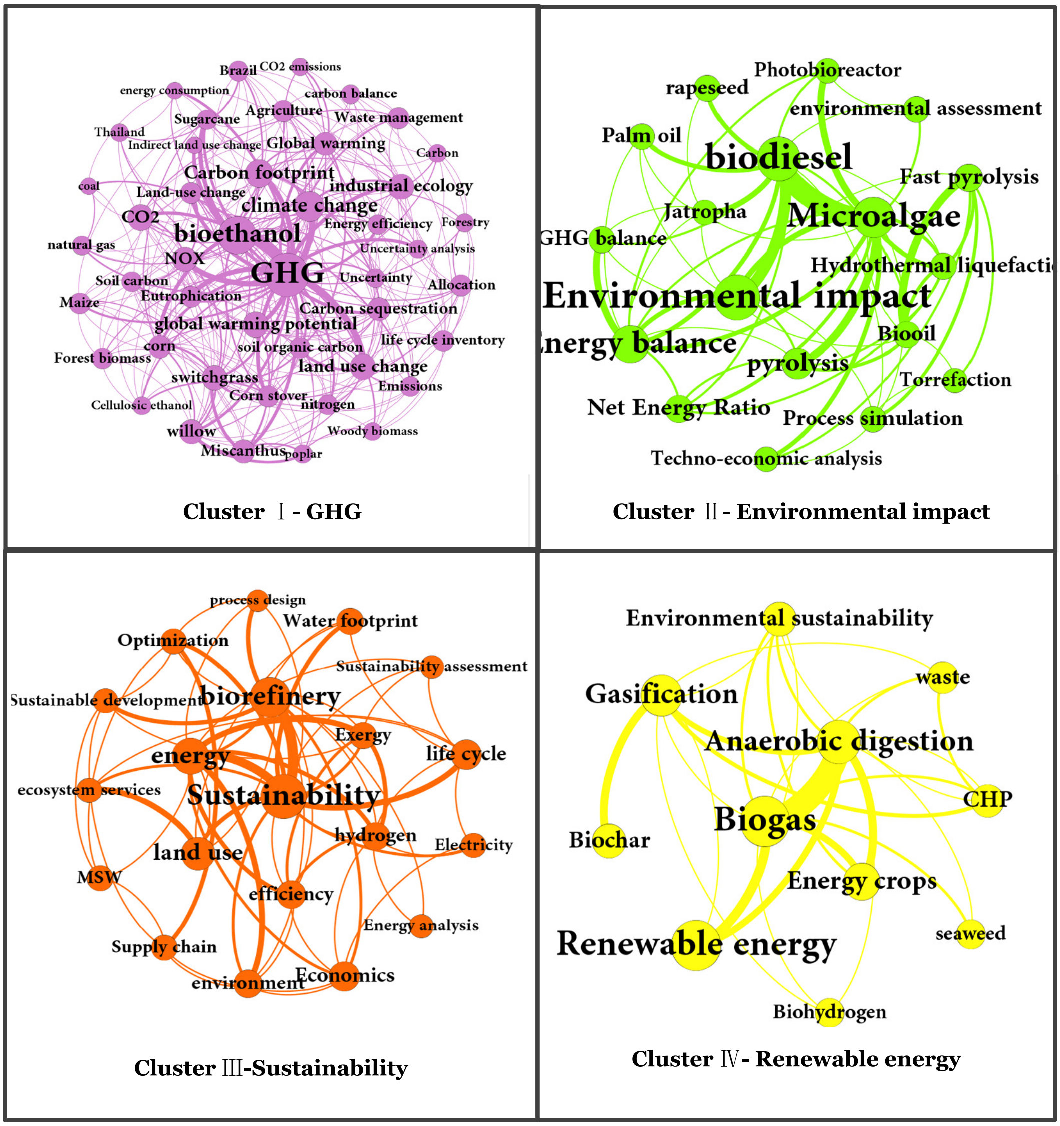

Fig. 5. Four categories of research topics in small world network.

(AD) and biogas production technology has grown rapidly over the years (Poeschl et al. 2012). Maybe in the future, it will grow to another hotspot in LCA for biomass.

4. Conclusion

This article discussed the key problems based on previous reviews of papers and publications concerning LCA for bioenergy. It concerns the keywords from 2367 publications about LCA for bioenergy during 2000–2017, providing a review on the evolution of research topics of LCA for bioenergy based on the SNA. We summarized several main innovative findings:

(1) The top 8 co-occurrence weight keywords with LCA could be classified into three categories: 1) the bioenergy production, including biodiesel, bioethanol, biogas and biorefinery; 2) environmental problems, including greenhouse gas, environmental impact and climate change; 3) environmental target, including sustainability. This means that LCA methods have been widely used in assessing the environmental impact from various types of bioenergy production process.

(2) The hot topic keywords and evolutionary co-words network at different stages were displayed. The results show that although“bioethanol” were the most significant hotspot of implication LCA from 2000 to 2011, its frequency has dropped down. However, the environmental performance of “biogas” and “land use” began to attract attention since 2015.

The LCA for bioenergy is the theme where the data collected are converted to environmental indicators such as human health, ecosystems, climate change and resources that describe the damage index of the materials or processes. The LCA is a comprehensive evaluation and stands at a higher level to make an overall assessment for biomass, rather than focus on a specific step or process. This paper provided bibliometric information to help understand the LCA method and direction of environmental impacts for bioenergy production process.

From a quantitative perspective, bibliometric technique provides a better understanding of the characteristics associated with body of literature related to LCA for bioenergy research. Bibliometrics provides a suite of indicators that can be combined to provide a useful picture for the development of LCA for bioenergy research, such as the co-occurrence network, the small world network and so on. Moreover,

the visualized SNA method adopted in this study provides an innovative tool which could be used in future bibliometric studies to analysis hot (cold) topic in renewable energy research fields. Thus, this research provides a useful reference for biomass fuel manufacturers, academics, biomass energy researchers, and policy decision makers.

Based on the conclusions, there are several agenda for future research: 1) it is essential to develop LCA methods for biogas and to conduct detailed environmental assessment. 2) The applications of LCA model in the bioenergy field need promote the techno-economic analysis for environmental impacts from bioenergy. 3) The regional or national differences as well as temporal differences in LCA for bioenergy should be paid more attention. 4) From the current outcomes, the energy efficiency of bioenergy is not highlighted by LCA. So, it is useful to consider the relationship between energy efficiency and LCA.

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